A DWT-entropy-ANN based architecture for epilepsy diagnosis using EEG signals

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A DWT-Entropy-ANN Based Architecture for Epilepsy Diagnosis Using EEG Signals

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***Abstract*—Electroencephalogram (EEG) is one the most common tools for epilepsy diagnosis and analysis. Currently, epilepsy diagnosis is still mainly performed by a neurologist through manual or visual inspection of EEG signals. In this article, we develop a computer aided diagnosis (CAD) for epilepsy based on discrete wavelet transform (DWT), Shannon entropy and feed-forward neural network (FFNN). DWT decompose EEG signals into several frequency sub-bands such as delta, theta, alpha, beta and gamma. Shannon entropy extract the EEG features from each these frequency sub-bands. Finally, FFNN classifies the corresponding EEG signals into "normal" or "epileptic" class based on the extracted features. Our experimental results using publicly available University of Bonn EEG dataset show perfect accuracy (100%).**

***Keywords*—epilepsy; computer aided diagnosis; EEG; DWT; entropy; ANN;**

I. Introduction

Electroencephalography (EEG) is a prominent medical tool for diagnosing and monitoring brain or neurological disorders such as epilepsy. About 65 million people worldwide have epilepsy [1]. Currently, epilepsy diagnosis is still performed primarily by a neurologist or skilled clinician through visual inspection of EEG signals. *Computer aided diagnosis* (CAD) has a tremendous potential to assist neurologists during the diagnosis process thus save the time and increase the accuracy.

EEG signal is non-stationary signal that mean applying Fourier transform directly to such signal is not practically suitable. Previous studies [2-4] have demonstrated the advantages of using *wavelet transform* (WT) for feature extraction from EEG signals. Using wavelet, EEG signals can be characterized by several frequency sub-bands: *delta* (<4 Hz), *theta* (4–8 Hz), *alpha* (8–13 Hz), *beta* (13–30 Hz), and *gamma* (>30Hz). The EEG signal is transformed into in multi-scale time-frequency domain by the wavelet to capture subtle changes in the signal.

Previous studies also showed the potential of using entropies to extract features directly from EEG segment [5, 6] or after wavelet transform [7, 8]. Various entropies have been studied for epilepsy diagnosis such as *spectral entropy*, *approximate entropy*, *sample entropy*, and *phase entropy*. Most of EEG analysis can be categorized classified into four groups [9]: time domain (e.g, linear discriminant analysis), frequency domain (e.g, Fourier transforms), time–frequency domain (e.g, wavelet), and nonlinear methods (e.g, largest Lyapunov exponent, entropies).

Although several promising EEG-based automatic epilepsy diagnosis methods have been proposed, further research efforts are still needed for clinical implementation. This research work aims to investigate a new epilepsy diagnosis method based on *discrete wavelet transform* (DWT), Shannon entropy and *feed-forward neural network* (FFNN). The remaining parts of this paper are organized as following: Section II explain the dataset used in this research work and also explain the methods for feature extraction and classification. Experimental results and discussion are provided in Section III. The last section concludes the paper and highlights the future research direction

II. Data and Methods

A. Data

The publicly available EEG dataset from University of Bonn presented in [10] is used in this work. The dataset contains five sets (named as set A–E). Every sets have 100 single-channel EEG segments (around 23.6 second). In this current research, we only use two sets: A and E. Set A as "normal class" and set E as "epileptic class". Figure 1 shows the typical EEG signals for each set.

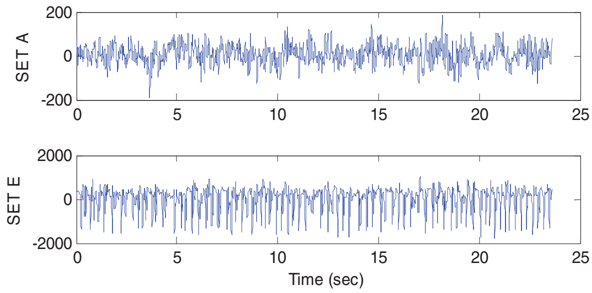

Fig. 1. Example for normal and epileptic EEG.

Set A contains EEG segments taken from normal subjects with eyes open, while set E was taken from EEG archive of epileptic subjects during seizure (or ictal) intervals. All data were recorded using the same EEG data acquisition (128-channel) with an average common reference. For detailed information about the data, the reader may refers to [10].

B. *Overview of the System*

The basic architecture of the proposed method is shown in Figure 2. At first, EEG segment as an input is fed to discrete wavelet transform (DWT). DWT decomposes the EEG segment into detail coefficients (D1-D5) and approximate coefficient (A5) that corresponding also to EEG sub-bands. Shannon entropy is then applied to these coefficients to reduce the dimension of the extracted features. Shannon entropy measures the distribution of the data. In total, six entropy values are extracted from an EEG segment, five from detail coefficients and one from approximate coefficient. Then, using the extracted features, feed-forward neural network (FFNN) classifies the corresponding EEG segment into "normal" or "epileptic" class. Detailed information about the methods are given in the next subsections.

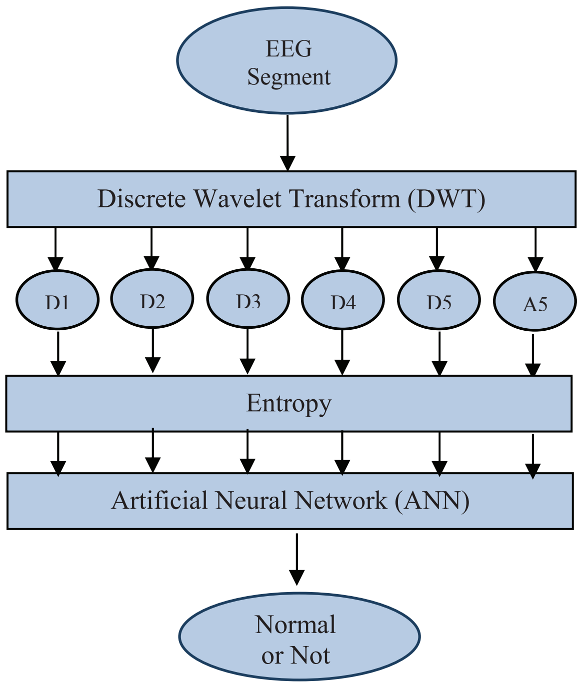

Fig. 2. Block diagram of EEG signal processing for epilepsy diagnosis.

C. *EEG Decomposition via wavelet*

Wavelet transform (WT) is able to represent the EEG signal in multi-scale time-frequency domain and captures subtle changes in the signal [2-4]. We adopted discrete wavelet transform (DWT) in this work. The DWT algorithm decomposes the EEG segment into approximation (A1) and detailed coefficient (D1) to obtain the first step of decomposition. The approximation coefficients in each step are further decomposed into approximation and detail coefficients. This process is repeated according to the number of decomposition level (see Figure 3).

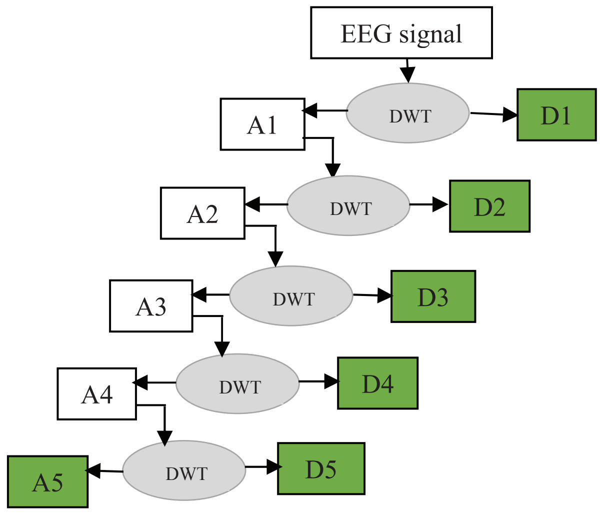

Fig. 3. EEG signal decomposition through 5-level DWT.

Selection of how many decomposition step is very crucial in discrete wavelet transform (DWT). The number of steps is selected according to the dominant frequency components of the signal. Following the previous works [11], since the most important frequency bands of the EEG signal are between 0-30 Hz, the decomposition level is selected to be 5 in this work. A recent review paper [4] showed that db4 is the most widely used and the authors suggested it is the most suitable for epilepsy diagnosis or seizure detection. Based on aforementioned reasons, db4 is adopted in this work. Figure 4 shows an example of approximation and details coefficients extracted from an EEG segment of epileptic subject (SET E).

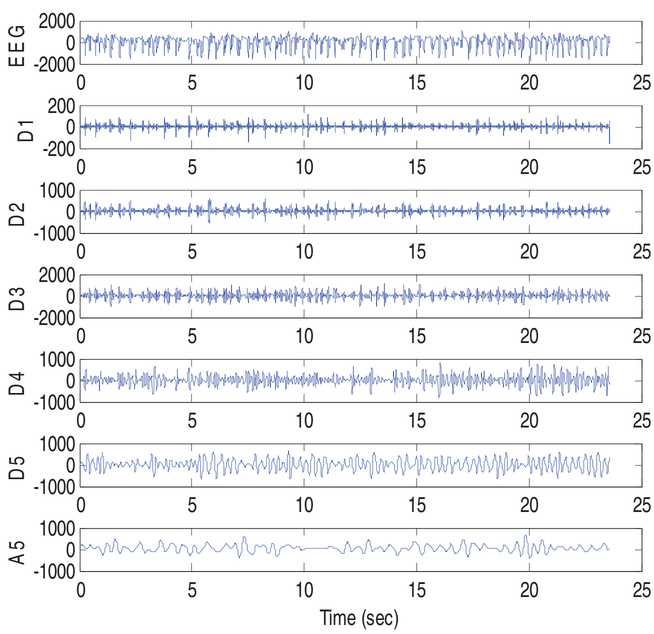

Fig. 4. Detail and approximate coefficients of an EEG segment.

D. Entropy

Entropy can be used to measure the complexity, regularity and the statistic quantification of time series data. Shannon entropy [12] is used in this work. Given time series data X=[x_1 x_2 ... x_N], Shannon entropy value can be obtained using the following formula:

$$H = -\sum_{i=1}^{k} p_i \log_2 p_i \quad (1)$$

In which k represents the number of unique values in the data (X) and p_i is the probability (or normalized frequency) for these unique values. Six entropy values are extracted from each EEG segment in which five from detail coefficients (D1-D5) and one from approximate coefficient (A5).

E. Classification Using ANN

The main goal of the classification process is to determine automatically the class of the EEG segment based on the extracted features. *Feed-forward neural network* (FFNN) is applied in this work for classifying the EEG segment based the extracted entropy value. We have designed FFNN with one input layer (with six nodes), one hidden layer (five nodes) and one output layer (two nodes) as shown in Figure 5. The number of nodes in the input layer equal is six, that corresponding to six input features.sig

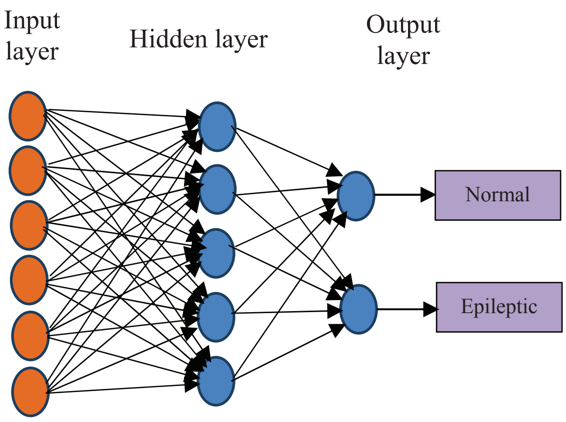

Fig. 5. ANN achitecture.

The hidden layer uses log-sigmoid transfer function, while output later uses soft max transfer function. FFNN must be trained first before it is used for classification or testing. The training process will adjust the weights and biases of the network. The performance of neural network depend on the 'epochs' process where epochs measure the number of iterations of the training vectors are used to update the weights of neurons and the performance of neural network is increased when epochs is increased. However, more epochs mean also increase the training time. We set the maximum epoch is equal to 200.

III. RESUTLS AND DISCUSSION

Several parameters are used to evaluate the classification performance of the proposed method such as sensitivity, specificity, and accuracy. These parameters are obtained using following formulas:

$$\text{Sensitivity} = \{TN/(FP+TN)\}*100 \quad (2)$$

$$\text{Specificity} = \{TP/(TP+FN)\}*100 \quad (3)$$

$$\text{Accuracy} = \{(TP+TN)/(TP+FP+TN+FN)\}*100 \quad (4)$$

In which, TP denotes the number of true positive diagnosis (that mean EEG segment from epileptic subject is correctly diagnosed as epileptic class). TN, FP and FN are for true negative, false positive and false negative diagnosis respectively.

For validation technique, a well-known 10-folds cross validation is used in all experiments. In the 10-fold cross-validation, the data is randomly grouped into 10 equal subsets. One subset is selected for test data, while the remaining subsets are applied for training. This process is repeated 10 times (folds) with other subset is selected as testing data. Each subset is exactly used one time as test data. The results of all experiment are averaged to produce a single classification performance.

Figure 6 shows the receiver operating characteristic (ROC) plot for the last test data. The area under the curve (AUC) is equal to one that means the classifier achieved perfect performance. The proposed method presented in this paper achieves perfect performance (100%) in term of sensitivity, specificity and overall accuracy. Table I presents summary of EEG-based epilepsy diagnosis that used the same dataset (set A vs set E). Several recent works also achieved perfect classification performance.

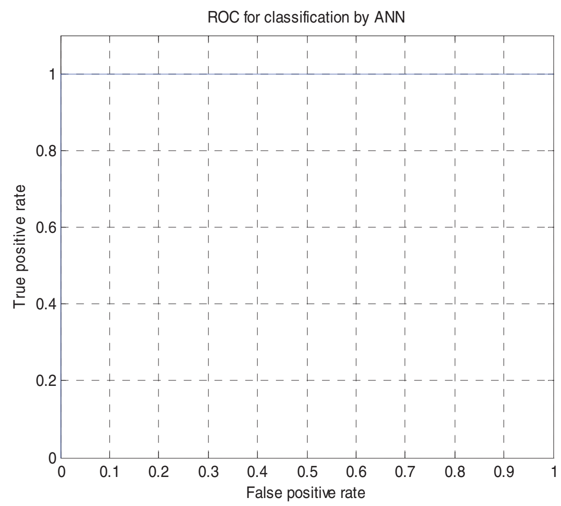

Fig. 6. ROC curves for ANN classifier.

TABLE I. SEVERAL EEG-BASED EPILEPSY DIAGNOSIS

Author	Feature Extraction	Classifier	Acc (%)
Niqam *et al* [13]	Non-linear filter	ANN	97.2
Kannathal *et al* [5]	Entropies	ANFIS	92.2
Subasi *et al* [11]	DWT	Mixture of expert (ME)	94.5
Srinivasan *et al* [6]	Approximate entropy (Apen)	Elman ANN	100
Ocak [7]	Apen on DWT	ANN	96
Dhiman *et al* [14]	DWT, GA-SVM	SVM	100
This work	DWT, Shannon entropy	ANN	100

Nigam and Graupe [13] proposed an EEG-based computer aided diagnosis of epilepsy using a nonlinear filtering for feature extraction and LAMSTAR ANN for classification. Their proposed technique achieved 97.2% accuracy. Kannathal *et al* [4] compared different entropy estimators and suggested that entropy values can distinguish normal EEG from epileptic EEG. They used *adaptive neuro fuzzy inference system* (ANFIS) for classification and achieved 92.2% accuracy. Srinivasan et al [6] achieved 100% accuracy by combining *approximated entropy* (ApEn) with Elman ANN classifier. Ocak [7] that also used approximated entropy for feature extraction but by combination with DWT. Over 96% accuracy was achieved with DWT and without it the accuracy was reduced as low as 73%.

Recently, Dhiman *et al* [14] employed several statistical properties on DWT coefficients and then optimal features were selected using *genetic algorithm* (GA) with *support vector machine* (SVM). However it seems that the computational effort was exhaustive. Instead on only classify set A and E, Nunes *et al* [15] have considered the whole dataset (Set A, B, C, D, E). They investigated several combinations of feature extraction and classification methods. They found the best performance using Coiflets wavelet as feature extractors and *optimum path forest* (OPF) as classifier which achieved 89.2% average accuracy.

One of the advantages of our proposed method is its simplicity. We use simple Shannon entropy that basically employs only arithmetic and log operations. The method was implemented using MATLAB R2009b on windows 7 PC with Intel i7 core @2.80GHz processor. Average processing time for DWT and Shannon entropy on one EEG segment are 1.2 and 0.5 ms (millisecond) respectively. Average processing time for one EEG segment features extraction is 11 ms. Average processing time for ANN training is 1.9 s (second), while for testing only 8.8 ms.

IV. CONCLUSIONS AND FUTURE DIRECTION

In this article, we have presented a new method for epilepsy diagnosis by using discrete wavelet transform (DWT), Shannon entropy and feed-forward neural network (FFNN). The proposed method achieved perfect accuracy (100%) evaluated by the public EEG dataset provided by the University of Bonn. The processing time was also fast enough. The futures works include testing the proposed method using larger and more comprehensive database. An adaptive learning will also be investigated to increase the system performance over the time.

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